Int J Life Cycle Assess (2013) 18:948–957
DOI 10.1007/s11367-012-0540-6

INPUT-OUTPUT AND HYBRID LCA

On the use of weighting in LCA: translating decision makers' preferences into weights via linear programming

Daniel Cortés-Borda · Gonzalo Guillén-Gosálbez · Laureano Jiménez Esteller

Received: 7 May 2012 / Accepted: 4 December 2012 / Published online: 23 January 2013

Abstract
Purpose The main goal of any life cycle assessment (LCA) study is to identify solutions leading to environmental savings. In conventional LCA studies, practitioners select from some alternatives the one which better matches their preferences. This task is sometimes simplified by ranking these alternatives using an aggregated indicator defined by attaching weights to impacts. We address here the inverse problem. That is, given an alternative, we aim to determine the weights for which that solution becomes optimal.
Methods We propose a method based on linear programming (LP) that determines, for a given alternative, the ranges within which the weights attached to a set of impact metrics must lie so that when a weighting combination of these impacts is optimized, the alternative can be optimal, while if the weights fall outside this range, it is guaranteed that the solution will be suboptimal. A large weight value implies that the corresponding LCA impact is given more importance, while a low value implies the converse. Furthermore, we provide a rigorous mathematical analysis on the implications of using weighting schemes in LCA, showing that this practice guides decision-making towards the adoption of some specific alternatives (those lying on the convex envelope of the resulting trade-off curve).
Results and discussion A case study based on the design of hydrogen infrastructures is taken as a test bed to illustrate the capabilities of the approach presented. Given are a set of production and storage technologies available to produce and deliver hydrogen, a final demand, and cost and environmental data. A set of designs, each achieving a unique combination of cost and LCA impact, is considered. For each of them, we calculate the minimum and maximum weight to be given to every LCA impact so that the alternative can be optimal among all the candidate designs. Numerical results show that solutions with lower impact are selected when decision makers are willing to pay larger monetary penalties for the environmental damage caused.
Conclusions LP can be used in LCA to translate the decision makers' preferences into weights. This information is rather valuable, particularly when these weights represent economic penalties, as it allows screening and ranking alternatives on the basis of a common economic basis. Our framework is aimed at facilitating decision making in LCA studies and defines a general framework for comparing alternatives that show different performance in a wide variety of impact metrics.

Keywords Hydrogen supply chains · Linear programming · Pareto optimality · Weighting

1 Introduction

A major goal in LCA studies is to identify from a set of alternatives that could potentially lead to environmental improvements the one to be finally implemented in practice. This task is in general straightforward when one option under study scores better than the rest in all the impact metrics simultaneously, but becomes difficult otherwise.

Multi-criteria decision making (MCDM) is a formal approach for solving problems of this type in which several conflicting criteria must be accounted for (Stewart 1992; Belton and Stewart 2002). This strategy works iteratively and typically comprises four steps: problem structuring, evaluation of the alternatives' performance, elicitation of decision

Responsible editor: Reinout Heijungs

D. Cortés-Borda · G. Guillén-Gosálbez (✉) · L. J. Esteller
Departament d'Enginyeria Química, Universitat Rovira i Virgili,
Av. Països Catalans, 26,
43007 Tarragona, Spain
e-mail: gonzalo.guillen@urv.cat

makers' preferences, and problem resolution (Gaudreault et al. 2009). MCDM can be broadly divided into multi-objective decision making (MODM) and multi-attribute decision making (MADM) (Geldermann and Rentz 2005).

MODM analyzes a search space restricted by constraints to identify the set of solutions representing the optimal compromise among the objectives considered in the analysis (Greening and Bernow 2004; Cohon 1978; Keeney and Raiffa 1976). Recently, MODM has been used in the context of LCA studies for automating the search for alternatives leading to environmental savings (Grossmann and Guillén-Gosálbez 2010).

In contrast, MADM is typically employed to select or evaluate a set of well-defined discrete alternatives in terms of a set of attributes. These methods can be used to assist practitioners in LCA studies, where several alternatives showing different performance in a set of impact metrics must be analyzed (Seppälä et al. 2001). In turn, MCDA methods can be divided into two groups: utility or value function-based methods and outranking methods (Lahdelma et al. 2000). Several authors have applied outranking methods in environmental decision making problems (Salminen et al. 1998; Norese and Toso 2004; Hermans et al. 2007), including LCA studies (Le Téno and Mareschal 1998; Geldermann and Rentz 2005). Particularly, approaches such as the ELECTRE (Roy 1991), PROMETHEE (Brans et al. 1986), GAIA (Brans and Mareschal 1994), AHP (Saaty 1980; Lippiatt and Fuller 2007), and TOPSIS (Yoon and Hwang 1985) have been used in environmental studies.

Aggregated environmental indicators represent another alternative to aid decision making in LCA studies. The use of weighting schemes in LCA requires quantifying and comparing the value of different environmental impacts (even when their units and scales differ), which represents a major challenge. Aggregated indicators are in practice calculated by attaching weights to a set of environmental impacts. These weights can be defined by a panel of experts or using some other methods (e.g., distance-to-target or monetarization). This approach facilitates the interpretation of a multi-dimensional system but has the drawback of being rather sensitive to the normalization and weighting scheme used.

A wide variety of weighting methods with different preference elicitation processes have been proposed in the literature. The Eco-indicator 95 (Goedkoop 1995) uses a weighted sum over three particular safeguard subjects. This aggregation step was criticized due to the subjectivity of the weighting and safeguard subjects. Particularly, Tietje et al. (1998) emphasized the importance of taking into account the differences in the perception of risks influencing the quantification of impacts. The Eco-Indicator 98 emerged to improve its predecessor by emphasizing on a better definition of damage categories along with a management system of value choices based on cultural perspectives (Goedkoop et al. 1998). Particularly, Hofstetter (1998) proposed to manage subjectivity using the cultural theory (Thompson et al. 1990) by considering only three perspectives in societal decision making: the individualist, egalitarian, and hierarchist. This consideration led to the Eco-indicator 99, an aggregated impact metric that follows this perspective approach. The use of perspectives leads to several versions of the methodology (Goedkoop and Spriensma 1999), and hence to different "best" options depending on the one used.

The evidence that LCA results may be subjective is clearly exposed by different surveys (see Hanssen 1999; Broberg and Christensen 1999), which showed that common LCA studies differ in the commercial software, LCA tools, characterization methods, impact assessment, and weighting schemes applied. Particularly, the authors identified up to six weighting methods that may lead to different practical results (Hanssen 1999). The relative importance of several environmental impacts and their aggregation into category indicators has attracted significant interest in the LCA literature (Huppes et al. 1997; Lindeijer1997; Mettier and Baumgartner 2000; Nagata et al. 1997; Walz et al. 1997; Onn and Yusoff 2010; Huppes et al. 2012). The general conclusion is that the outcomes of the LCA studies may be biased.

Bearing in mind the subjectivity of many LCA approaches, some authors have proposed methods to avoid value-lading on environmental criteria. Hofstetter et al. (1999) introduced a ternary diagram to graphically represent the areas in which, depending on the weighting combination, one solution behaves better than the rest. This methodology was later used in other studies that attempted to avoid the subjectivity implied in weighting (Almeida et al. 2007; Lesage et al. 2007; Barbiroli et al. 2008). The main drawback of this approach is that it restricts the analysis to only three environmental indicators that are represented in a two dimensional plot. Furthermore, this analysis is somehow straightforward when a reduced number of solutions is considered but may become cumbersome as we increase the number of objectives and solutions.

In this article, we present a method to facilitate decision making in LCA studies that addresses the problem backwards. That is, given a solution (or set of solutions) proposed for improving the LCA performance of a system, we aim at finding the lower and upper limits of the intervals within which the weights to be attached to a set of LCA impacts must fall so that the selected solution becomes optimal over the rest of alternatives. To the best of our knowledge, this is the first approach that addresses decision making in LCA in an inverse manner. Adopting this reverse approach allows calculating the monetary units (i.e., economic penalties) that decision makers are willing to pay for the damage caused when a given alternative is chosen. Note that our approach provides an outcome similar to that

generated by environmental monetization and valuation (Bockstael et al. 2000; Farrow et al. 2000; Kahneman and Knetsch 1992) or sensitivity analysis of LCA outcomes (Guinée et al. 2002), but instead of using economic estimations, it relies on a systematic mathematical approach. The information generated by our analysis is valuable for decision makers, as it allows ranking alternatives on a common scoring system based on monetary units. Our approach is based on linear programming (LP) tools and can be applied efficiently to problems involving up to thousands of solutions and hundreds of environmental indicators.

2 Methods

2.1 Illustrative example

To motivate our approach, let us consider an illustrative example with six solutions (1 to 6) and two impact metrics (IMP1 and IMP2). Figure 1 depicts the solutions in the space of the two environmental indicators. As observed, point 4 is suboptimal since point 3 shows lower values in both LCA impacts than 4. Further reductions in the set of solutions are not possible, since the remaining alternatives are all Pareto optimal. That is, there is no one improving any of the others simultaneously in both LCA impacts (i.e., there is no solution that dominates any of the others). Note that we use here the mathematical definition of Pareto optimality (see for instance Ehrgott 2005). According to this, a solution "A" is said to be Pareto optimal if there is no other solution that performs better than "A" in at least one objective without necessarily worsening at least any other criterion.

A common approach to choose between the set of Pareto optimal points (i.e., all except alternative 4) consists of minimizing a weighted sum of the two indicators, thereby simplifying the associated decision making process. Aggregated metrics are typically expressed as a linear combination of the individual impacts as follows:

$$AIMP = w_1 \cdot IMP_1 + w_2 \cdot IMP_2$$

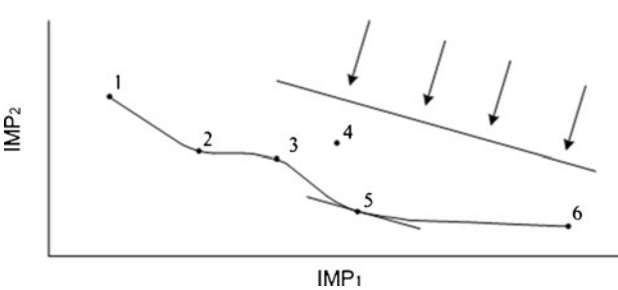

Fig. 1 Six solutions (*dots 1–6*), the Pareto front (*curved line*), and an iso-preference line (*straight line*) for the case of two environmental indicators

Where AIMP is the aggregated indicator, IMP_i represents the value of LCA impact i, and w_i is the corresponding weight. Figure 1 illustrates the graphical meaning of using these weights for optimization purposes. As observed, the solution obtained by optimizing a given weighted combination of impacts is the intersection between the straight line with slope $-w_2/w_1$ and the curve that trades-off both environmental indicators (i.e., the Pareto front IMP_1 vs IMP_2). In the figure, the weighted sum is represented by a straight line. The minimization problem seeks to push this line towards the origin until it intersects the convex region on the boundary. Depending on the weighting values, different points can emerge as optimal solutions. This is shown in Table 1, in which various w_2/w_1 ratios (R_1 to R_5) are considered.

As observed in Table 1, the weighting scheme has a major impact on decision making. The underlined values shown in the table represent the optimal solutions obtained for each combination of weights. It can be clearly observed how the optimum solution changes from one point to another according to different weighting values. An important remark is that despite being Pareto optimal, solution 3 cannot be generated by minimizing any aggregated indicator, regardless of the weighting scheme of choice. This is because this point lies in the non-convex region of the trade-off curve (see details in Ehrgott 2005). The same holds for solution 4, but in this case, the reason is that this solution is not Pareto optimal, so it can be discarded from the pool (solution 2 is better than solution 4 in both metrics simultaneously).

Given a set of alternatives and the corresponding LCA impacts, our goal is to determine the minimum and maximum values of the weights to be attached to each damage category such that within this range the solution can become optimal, while if any of them falls outside this interval, the alternative is guaranteed to be suboptimal. These bounds provide valuable insight regarding the weights that practitioners implicitly consider when they select a given alternative. Furthermore, when

Table 1 Results of the weighted sum for different weighting ratios (the optimal solution for each weighted combination of weights is underlined) and their corresponding minimum and maximum weight values (w_2) for the illustrative example

	R_1 0.1	R_2 0.3	R_3 1	R_4 2	R_5 3	Min w_2	Max w_2
1	<u>6</u>	14	42	82	122	0	0.23
2	7.7	<u>13.1</u>	32	59	86	0.23	0.38
3	10.4	15.2	32	56	80	–	–
4	12.8	18.4	38	66	94	–	–
5	12.1	14.3	<u>22</u>	<u>33</u>	44	0.38	2.33
6	18.8	20.4	26	34	<u>42</u>	2.33	Inf

the cost is included in the analysis, these weights represent the economic penalties that decision makers are willing to pay for a unit of impact.

2.2 Linear programming

Our approach is based on LP tools. We are given a set J of solutions and the environmental impact associated to each of them (quantified according to some LCA indicators). From now on, we assume that we would like to minimize all the impact metrics simultaneously (the case in which an impact metric, like energy saving or recyclability, must be maximized can be easily handled by reversing the sign of this impact indicator in the objective function). We further assume that the final solution to be implemented in practice is identified by minimizing a weighted sum of these impacts. The goal of the analysis is then to determine for every solution j and impact category i, the lower and upper limits of the interval [$\underline{w}_{i,j}$, $\overline{w}_{i,j}$] such that if the weight attached to the category falls outside the interval, then the solution will be guaranteed to be suboptimal (i.e., the solution will not be selected if the weight falls outside this interval). The limits of this interval are obtained by solving the following LP models:

$$\overline{w}_{i,j} = \max w_i$$

$$s.t. \sum_i w_i \cdot \mathrm{IMP}_{i,j} \leq \sum_{\mathrm{i}} \mathrm{w_i} \cdot \mathrm{IMP}_{i,j'} \ \forall \mathrm{j} \neq \mathrm{j}' \tag{1}$$

$$w_i^{LO} \leq w_i \leq w_i^{UP} \tag{2}$$

$$\underline{w}_{i,j} = \min w_i$$

$$s.t. \sum_i w_i \cdot \mathrm{IMP}_{i,j} \leq \sum_{\mathrm{i}} \mathrm{w_i} \cdot \mathrm{IMP}_{i,j'} \ \forall \mathrm{j} \neq \mathrm{j}' \tag{3}$$

$$w_i^{LO} \leq w_i \leq w_i^{UP} \tag{4}$$

where parameter $\mathrm{IMP}_{i,j}$ denotes the value of impact i in solution j. Eqs. (1) and (3) ensure that solution j shows better aggregated impact than the remaining alternatives j', while constraints 2 and 4 force the weights to lie between some lower and upper limits that should be defined according to external restrictions. Note that the lower limit on the weight should be greater than 0, thereby enforcing a positive weight.

A pre-filtering step can be applied prior to the calculation of the LP in order to discard suboptimal solutions (i.e., those alternatives improved by at least another one in all of the objectives considered simultaneously). Note, however, that this step can be skipped, since the LP model will render infeasible for such solutions (i.e., there will be no combination of weights for which a suboptimal Pareto solution will become optimal).

As an illustrative example, let us consider the solution number 1 from Table 2. For clarification purposes, we will assume in this particular example that IMP_1 is the cost in US dollar (USD) of a given product and IMP_2 are the kilograms of CO_2 associated with the production of such a product. Solution 1 is the cheapest alternative but also the most polluting option. Clearly, choosing this alternative as the "best" implies that IMP_1 is given more importance than IMP_2. To find the minimum and maximum weights that drive this decision, we apply our LP-based approach based on Eqs. (1) to (4). For this example, we need to define the following equations:

$$\begin{aligned}
\overline{w}_{i,j} = \quad & \max \quad w_2 \\
& s.t. \quad 1 \cdot 2 + w_2 \cdot 40 \leq 1 \cdot 5 + w_2 \cdot 27 \\
& \qquad 1 \cdot 2 + w_2 \cdot 40 \leq 1 \cdot 8 + w_2 \cdot 24 \\
& \qquad 1 \cdot 2 + w_2 \cdot 40 \leq 1 \cdot 10 + w_2 \cdot 28 \\
& \qquad 1 \cdot 2 + w_2 \cdot 40 \leq 1 \cdot 11 + w_2 \cdot 11 \\
& \qquad 1 \cdot 2 + w_2 \cdot 40 \leq 1 \cdot 18 + w_2 \cdot 8 \\
& \qquad 0 \leq w_2 \leq 10^6
\end{aligned}$$

$$\begin{aligned}
\overline{w}_{i,j} = \quad & \min \quad w_2 \\
& s.t. \quad 1 \cdot 2 + w_2 \cdot 40 \leq 1 \cdot 5 + w_2 \cdot 27 \\
& \qquad 1 \cdot 2 + w_2 \cdot 40 \leq 1 \cdot 8 + w_2 \cdot 24 \\
& \qquad 1 \cdot 2 + w_2 \cdot 40 \leq 1 \cdot 10 + w_2 \cdot 28 \\
& \qquad 1 \cdot 2 + w_2 \cdot 40 \leq 1 \cdot 11 + w_2 \cdot 11 \\
& \qquad 1 \cdot 2 + w_2 \cdot 40 \leq 1 \cdot 18 + w_2 \cdot 8 \\
& \qquad 0 \leq w_2 \leq 10^6
\end{aligned}$$

Where the search space for w_2 is between 0 and a large number (in this case 10^6). w_1 was set to 1 on purpose so that, after solving the LPs, the w_2/w_1 ratio represent the economic penalty (USD) that decision makers are willing to pay per kilogram of CO_2. Bearing this in mind, the results of the LPs (see Table 1) are interpreted as follows: if decision makers would be willing to pay from 0 to 0.23 USD per kilogram of CO_2, then solution 1 would be optimal. If decision makers were willing to pay a little bit more for unit of CO_2 polluted, then they should choose solution 2.

Table 1 shows the results of applying our approach to the motivating example, assuming w_1 is fixed to one. As observed, there is no combination of weights for which

Table 2 Set of solutions considering two impact metrics

	IMP1	IMP2
1	2	40
2	5	27
3	8	24
4	10	28
5	11	11
6	18	8

solutions 3 and 4 are optimal. Furthermore, solutions located on the right hand side of the curve show large weights, while these weights decrease as we move to the left. This is consistent with the fact that these solutions (points 5 and 6) show less IMP_2 values.

Let us finally note that the LPs introduced before might render infeasible if there is no weighting combination for which a given solution is optimal (e.g., solutions 3 and 4 in Fig. 1). This may happen, for instance, when an alternative is either suboptimal in the space of the environmental indicators or it lies in the non-convex part of the Pareto set.

3 Numerical results

As benchmark problem to illustrate the capabilities of our approach, we consider the multi-objective optimization of hydrogen supply chains (SC) for vehicle use. A description of the problem under study is given elsewhere (Sabio et al. 2010), including a detailed LCA study on several production, storage, and manufacturing technologies to produce hydrogen. Given are a hydrogen demand, fixed time horizon, set of time periods, production, and storage technologies available, capacity limitations of plants and storage facilities, operating and facility investment costs, and interest rate. The goal is to minimize the total cost of the infrastructure and the associated impact, which is quantified according to three LCA indicators. Note that the interest here is on the application of our approach to a set of design alternatives for producing and delivering hydrogen rather than on discussing their main structural features. Details on the latter topic can be found in the work by Sabio et al. (2012).

A superstructure of alternatives is considered, from which the best ones must be identified. Particularly, we consider three technologies to produce hydrogen (i.e., steam methane reforming, coal gasification, and water electrolysis) and two storage technologies (i.e., compressed hydrogen storage and liquefied hydrogen storage). In this work, we use a simplified version of the mixed-integer linear programming (MILP) optimization model for hydrogen SCs described in Sabio et al. (2010) for generating alternative designs each achieving a unique combination of LCA indicators. From these solutions, decision makers should choose the best ones according to their preferences. The aforementioned MILP includes three types of variables: continuous, binary, and discrete. The first are used to model mass flow rates and capacities of plants and warehouses, while binaries are employed to denote the execution of capacity expansions and the establishment of transportation links. Discrete variables denote the number of plants and types of technologies selected. Note that, for the sake of simplicity, we focus on selecting the type of technologies and not their spatial locations.

We used the epsilon constraint method (Haimes et al. 1971) to generate a set of Pareto solutions (i.e., network designs leading to different LCA indicators) that were taken as a basis in our LP approach. The epsilon constraint method is a multi-objective solution algorithm based on solving a set of single-objective models obtained from the original multi-objective one by keeping one criterion in the objective function and transferring the rest to auxiliary constraints that bound them within some allowable limits. Particularly, we calculated a set of bi-criteria problems using this method where the cost was traded-off against each single impact separately. That is, we minimized the cost of the network for different limits on a given environmental impact and then repeated the same type of calculations for the other impacts. We finally identified 30 Pareto optimal design alternatives (ten solutions in each bi-criteria problem), each showing a unique combination of values for the economic and LCA indicators considered in the analysis and entailing a set of production and storage technologies. Further details on the epsilon constraint method can be found elsewhere (Ehrgott 2005), while details on how to apply this method to the problem of interest are available in Sabio et al. (2010).

The LCA impact of each alternative was quantified according to the Eco-indicator 99 framework. The life cycle inventory was determined from the production rates of hydrogen and the amount of hydrogen stored using algebraic equations and information retrieved from Eco-invent (see Sabio et al. 2012, for further details).

We should remark that it is possible to generate the set of alternatives used for decision making and employed in our approach by means of different strategies (e.g., rules of thumb, heuristics, optimization, etc.). For the purpose of our study, it suffices with an initial set of feasible alternatives, each showing a unique combination of economic and environmental metrics values. In common LCA practice, these alternatives should be defined by decision makers based on previous knowledge on the system. Furthermore, even though we have used a rigorous optimization model to generate these design alternatives, in the more general case, we do not assume herein the existence of such a model for the system under study.

Figures 2, 3, and 4 show the projections of the 30 solutions onto a set of 2-D subspaces (i.e., cost vs each damage category separately). More precisely, each plot depicts the ten Pareto optimal solutions obtained by optimizing each impact vs. the cost, plus 20 more points resulting from the calculation of the remaining bi-criteria Pareto sets. As seen, only some of the 20 projections lie above the Pareto curves obtained in the 2D subspace. It can also be observed how some points belonging to different bi-criteria Pareto sets overlap.

In the minimum cost solution, hydrogen is produced via steam methane reforming and stored as a liquid. In the

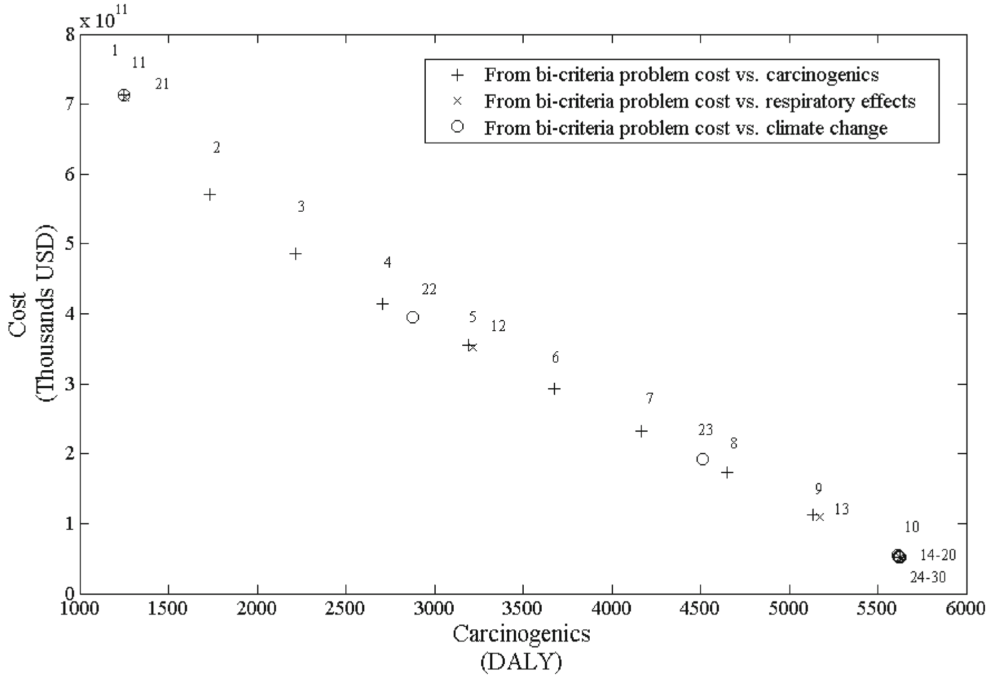

Fig. 2 Bi-criteria Pareto plot: cost vs carcinogenics. *Numbers on the points* correspond to those shown in Table 3

minimum impact solutions (i.e., minimum human health, ecosystem quality, and depletion of resources), hydrogen is produced through water electrolysis and stored in gas phase. For the sake of brevity, the reader is referred to the original publication by Sabio et al. (2012) for further details on the solutions obtained.

As a first step, we applied our approach to each bi-criteria set of solutions separately, that is, to each Pareto set calculated by optimizing a different environmental impact against the cost. In all of the runs, the weight associated with the cost was fixed to one. The LPs were implemented in GAMS and solved with the solver CPLEX 12.2.0.2. Each LP contains two variables, which are the weights of the economic objective and one of the three environmental objectives. It took around 0.015 CPU seconds to solve a single LP instance using an AMD Phenom Triple-core 2.29 GHz processor.

As seen, there are some points (e.g., solutions 5, 7, and 8, among others) in Figs. 2 to 4 that will never become optimal when optimizing the cost and the environmental impact

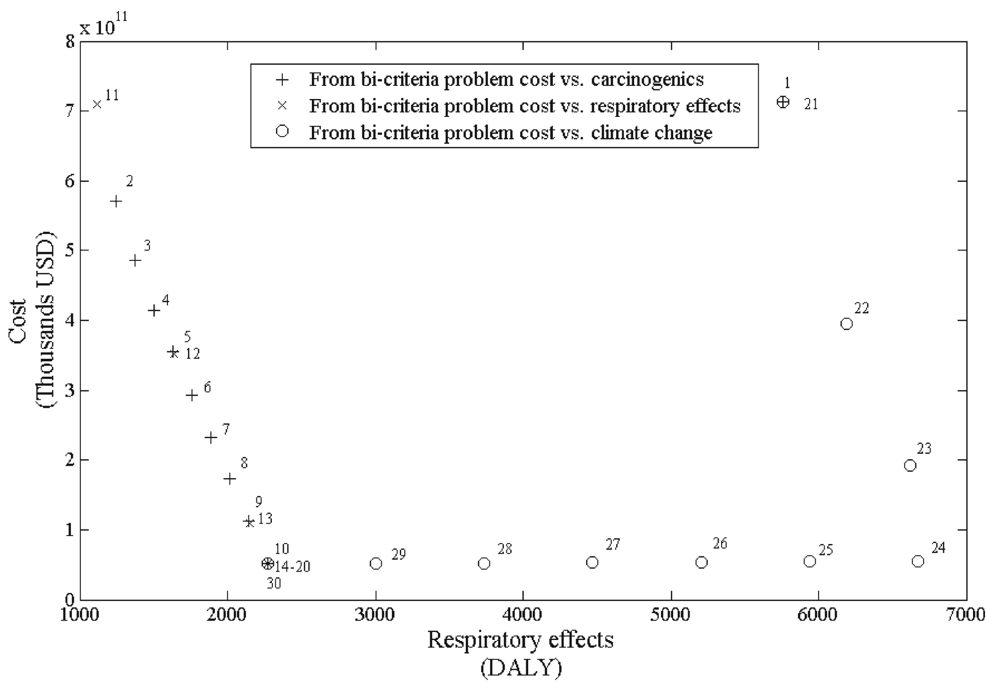

Fig. 3 Bi-criteria Pareto plot: cost vs respiratory effects. *Numbers on the points* correspond to those shown in Table 3

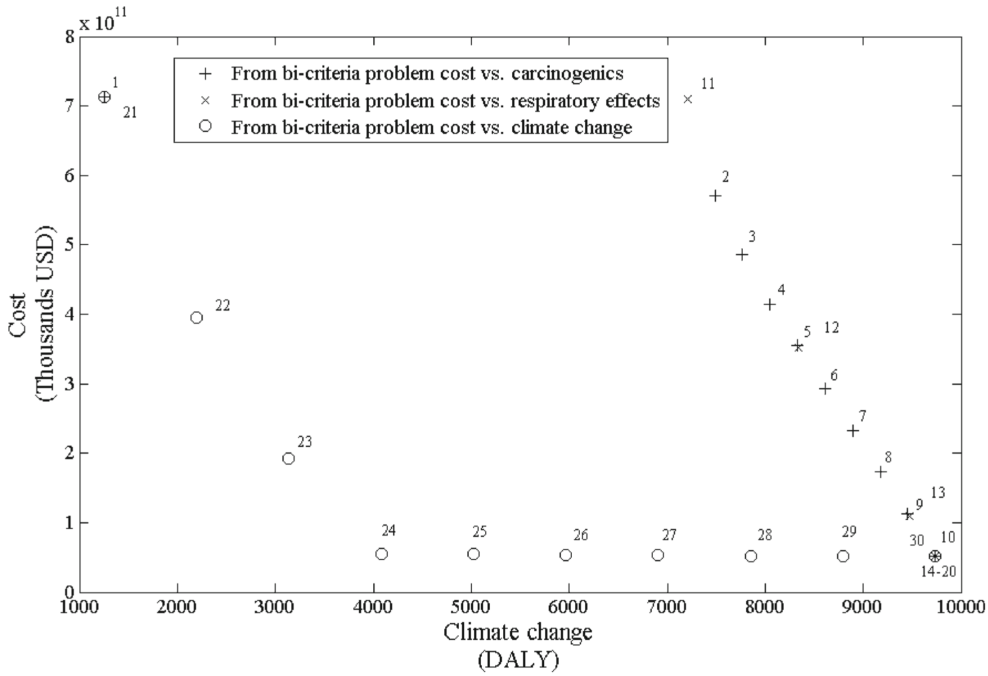

Fig. 4 Bi-criteria Pareto plot: cost vs climate change. *Numbers on the points* correspond to those shown in Table 3

simultaneously independent of the weights used. This is because these solutions belong to the non-convex part of the Pareto front. Table 3 displays the maximum and minimum weights outside which each Pareto solution becomes suboptimal. Note that some solutions which are optimal in one criterion perform significantly worse in the others. That is, the points of a given Pareto set optimized for one LCA indicator may be suboptimal for a different LCA metric.

As mentioned before, our LP-based approach finds the upper and lower bounds of the weight range within which an alternative can become optimal among others. These bounds represent the maximum and minimum economic penalties that decision makers would be willing to pay for each alternative. Some authors refer to this as the environmental valuation or monetization (Turner et al. 1993). As observed, these bounds on the weights increase in a single direction over the curves. Thus, in the extreme solutions in which the environmental impact is minimized, the weights take their maximum value. In other words, a very large cost per unit of impact is considered, and such high penalty drives the optimization

Table 3 Results of applying the LP approach to each bi-criteria Pareto set separately

	Cost (kUSD)	Carcinogenics			Respiratory effects			Climate change		
		Impact (DALY)	Weights on carcinogenics (kUSD/DALY)		Impact (DALY)	Weights on respiratory effects (kUSD/DALY)		Impact (DALY)	Weights on climate change (kUSD/DALY)	
			Min	Max		Min	Max		Min	Max
1, 21	7.13E+8	1,247.583	381,992.98	1.00E+11	5,760.537	–	–	1,252.42	336,517.24	1.00E+11
2	5.72E+8	1,733.767	174,485.47	288,915.38	1,243.995	66,214.37	109,638.64	7,488.543	–	–
3	4.87E+8	2,219.95	147,171.69	174,485.47	1,372.112	55,849.24	66,214.37	7,769.559	–	–
4	4.15E+8	2,706.133	125,362.63	147,171.69	1,500.23	47,573.06	55,849.24	8,050.574	–	–
6	2.93E+8	3,678.499	124,497.82	125,362.63	1,756.464	47,244.88	47,573.06	8,612.605	–	–
10, 14–20, 30	5.11E+7	5,623.232	0.00	124,497.82	22,689.32	0.00	47,244.88	9,736.67	0.00	745.96
11	7.09E+8	1,256.69	288,915.38	381,992.98	11,182.78	10,9638.64	1.00E+10	7,212.79	–	–
22	3.96E+8	2,878.533	–	–	61,903.18	–	–	2,195.11	214,735.63	336,517.24
23	1.93E+8	4,509.482	–	–	66,201	–	–	3,137.81	146,135.43	214,735.63
24	5.54E+7	5,614.59	–	–	66,742.58	–	–	4,080.50	769.45	146,135.43
25	5.47E+7	5,616.031	–	–	59,400.37	–	–	5,023.20	762.82	769.45
27	5.32E+7	5,618.911	–	–	44,715.95	–	–	6,908.58	760.89	762.82
28	5.25E+7	5,620.351	–	–	37,373.74	–	–	7,851.28	745.96	760.89

towards solutions with a low impact. In contrast, in the minimum cost solution, the weights are rather low.

We applied next our approach to the entire set of alternatives considering simultaneously the cost and the three environmental objectives. The LPs contain four variables, which in this particular case are the weight of the economic objective and the weights of the three environmental objectives. Each LP took around 0.047 CPU seconds in the same computer.

In this multi-criteria case study, there are 22 feasible solutions (considering the repeated solutions) that can be optimal under certain weighting combinations, whereas in the bi-criteria case, there were only 17. Thus, discarding alternatives according to optimality principles becomes more difficult as we include more objectives in the multi-criteria analysis. This is because solutions that perform poor in some indicators may perform well in others, so the more indicators we consider, the more chances there are for a solution to show better performance than the rest in certain environmental categories.

Table 4 shows the maximum and minimum weights for each alternative considering the four objectives. Similarly to the bi-criteria case studies, it was found that certain solutions are always suboptimal independent of the combination of weights. Note that in the multi-criteria approach, the boundaries of the "optimal region" become weaker, as they depend as well on the weights attached to other LCA impacts. That is, the weight intervals become wider: the lower bound is decreased and the upper bound is increased. This is because in this second case other impacts and weights come into play, so there are more chances for a solution to become optimal as we consider a larger set of weights. Let us note that the optimality of a solution is not guaranteed even when the weights are within the limits found by the algorithm, as we need to check as well the weights defined for the remaining impact categories. It can be ensured, however, that outside such an interval the solution will never be optimal.

4 Discussion

The weighting intervals for three bi-criteria case studies are given in Table 3, while Table 4 shows the same values for the multi-criteria case. These weights represent the economic penalties that decision makers are willing to pay when choosing a given alternative. This could be understood as the valuation or monetization of the environmental impact (see Bockstael et al. 2000; Farrow et al. 2000; Kahneman and Knetsch 1992). Monetization, and in general the value laden approaches of LCA, has been criticized due to the moral implications associated to giving monetary value to the environment and/or biasing the interests of decision makers. By addressing the problem in an inverse manner, the valuation of impacts is not imposed by decision makers. Instead, we calculate ranges for the weights attached to the impacts in a systematic manner using an LP model. This approach assesses in a systematic manner the pool of alternatives from which practitioners should select the best one according to their preferences, providing valuable information for them.

After running the algorithm, it was found that certain solutions are suboptimal independent of the weighting combination. This could be attributed to two reasons: the

Table 4 Results of applying the LP approach to the whole set of Pareto solutions simultaneously

	Carcinogenics (DALY)	Respiratory effects (DALY)	Climate change (DALY)	Cost (kUSD)	Carcinogenics		Respiratory effects		Climate change	
					Weights on carcinogenics (kUSD/DALY)		Weights of respiratory effects (kUSD/DALY)		Weights on climate change (kUSD/DALY)	
					Min	Max	Min	Max	Min	Max
1, 21	1,247.583	5,760.537	1,252.42	7.13E+8	0.00	1.00E+11	0.00	1.00E+13	0.00	1.00E+11
2	1,733.767	1,243.995	7,488.543	5.72E+8	0.00	288,915.38	0.00	109,639.00	0.00	315,507.79
3	2,219.95	1,372.112	7,769.559	4.87E+8	0.00	174,485.47	0.00	66,214.37	0.00	191,989.73
4	2,706.133	1,500.23	8,050.574	4.15E+8	0.00	147,171.69	0.00	55,849.24	0.00	161,052.56
6	3,678.499	1,756.464	8,612.605	2.93E+8	0.00	125,362.63	0.00	47,573.06	0.00	137,007.19
10, 14–20, 30	5,623.232	2,268.932	9,736.667	5.11E+7	0.00	124,497.83	0.00	47,244.88	0.00	136,105.80
11	1,256.69	1,118.278	7,212.791	7.09E+8	0.00	1.00E+11	0.00	1.00E+13	0.00	7.79E+10
22	2,878.533	6,190.318	2,195.114	3.96E+8	0.00	189,970.79	0.00	26,594.37	348.85	33,6517.24
23	4,509.482	6,620.1	3,137.808	1.93E+8	0.00	122,981.91	0.00	17,216.47	1965.35	214,735.63
24	5,614.59	6,674.258	4,080.502	5.54E+7	0.00	123,936.47	0.00	17,350.10	580.10	146,135.43
25	5,616.031	5,940.037	5,023.197	5.47E+7	–	–	–	–	–	–
27	5,618.911	4,471.595	6,908.585	5.32E+7	–	–	–	–	–	–
28	5,620.351	3,737.374	7,851.279	5.25E+7	0.00	123,977.56	0.00	17,355.86	556.54	135,922.75

alternative is Pareto suboptimal (i.e., there is another alternative that improves it in all the objectives simultaneously) or it lies in the non-convex region of the Pareto front. The range within which the solutions are optimal becomes wider as we increase the number of objectives.

Expressing the alternatives that are evaluated according to several impact indicators on a common basis (money per unit of impact) simplifies the decision making procedure, as it allows objective comparisons using a single (and more tangible) indicator. Furthermore, it allows identifying tendencies in which weights increase and decrease. The solution sought should show a good balance between weights, and therefore a good performance on average in all the indicators.

5 Conclusions

LCA practitioners must choose among several alternatives considering several environmental impact indicators, which makes decision making a difficult task. While aggregated LCA methods can simplify decision making to a large extent, they have been severely criticized for being biased and reflecting the views of a small number of experts. In the present work, we proposed a systematic LP-based method that supports decision making in LCA. Our algorithm systematically provides valid weights ranges within which the solutions are potentially optimal, while at the same time discarding alternatives that are guaranteed to be suboptimal for every possible combination of weights.

This algorithm addresses the weighting problem in an inverse manner. Hence, decision makers are not required to provide weights beforehand, since the intervals within which these weights should fall are automatically calculated by the algorithm on the basis of the alternatives available. Our approach allows expressing several objectives on a common basis (money per unit of impact), which makes it easier to check whether the alternatives are consistent with the decision makers' preferences. Our final aim is to facilitate decision making in LCA studies, placing particular emphasis on problems with a large number of alternatives and objectives to be considered.

Acknowledgments The authors wish to acknowledge the support from the Spanish Ministry of Education and Science (project nos. DPI2008- 04099, CTQ2009-14420-C02, DPI2012-37154-C02-02, and CTQ2012-37039-C02-01) and the Spanish Ministry of External Affairs (project nos. A/023551/09 and HS2007-0006).

References

Almeida CM, Barrella FA, Giannetti BF (2007) Energetic ternary diagrams: five examples for application in environmental accounting for decision-making. J Cleaner Prod 15(1):63–74

Barbiroli G, Candela G, Raggi A (2008) Implementing a new model to measure and assess eco-effectiveness as an indicator of sustainability. Int J Sus Dev World Ecol 15(3):222–230

Belton V, Stewart T (2002) Multiple criteria decision analysis: an integrated approach. Kluwer Academic, Boston

Bockstael NE, Freeman AM III, Kopp RJ, Portney PR, Smith VK (2000) On measuring economic values for nature. Env Sci Tech 34(8):1384–1389

Brans JP, Mareschal B (1994) The PROMCALC & GAIA decision support system for multicriteria decision aid. Decis Support Syst 12(4–5):297–310

Brans JP, Vincke P, Mareschal B (1986) How to select and how to rank projects: the promethee method. Eur J Oper Res 24(2):228–238

Broberg O, Christensen P (1999) LCA experiences in Danish industry: results of a survey. Int J Life Cycle Assess 4(5):257–262

Cohon J (1978) Multiobjective programming and planning. Academic, New York

Ehrgott M (2005) Multicriteria optimization. Springer, Berlin

Farrow RS, Goldburg CB, Small MJ (2000) Economic valuation of the environment: a special issue. Environ Sci Technol 34(8):1381–1383

Gaudreault C, Samson R, Stuart P (2009) Implications of choices and interpretation in LCA for multi-criteria process design: de-inked pulp capacity and cogeneration at a paper mill case study. J Cleaner Prod 17(17):1535–1546

Geldermann J, Rentz O (2005) Multi-criteria analysis for technique assessment: case study from industrial coating. J Ind Ecol 9 (3):127–142

Goedkoop MJ (1995) The Eco-lndicator 95. Final report. PRé Consultants, Amersfoort

Goedkoop M, Spriensma R (1999) The Eco-indicator 99: a damage oriented method for life cycle impact assessment. Methodology report, Amsterfort

Goedkoop M, Hofstetter P, Müller-Wenk R, Spriemsma R (1998) The eco-indicator 98 explained. Int J Life Cycle Assess 3(6):352–360

Greening LA, Bernow S (2004) Design of coordinated energy and environmental policies: use of multi-criteria decision-making. Energ Policy 32(6):721–735

Grossmann IE, Guillén-Gosálbez G (2010) Scope for the application of mathematical programming techniques in the synthesis and planning of sustainable processes. Comp Chem Eng 34(9):1365–1376

Guinée JB, Gorrée M, Heijungs R, Huppes G, Kleijn R, de Koning A, van Oers L, Wegener Sleeswijk A, Suh S, Udo de Haes HA, de Bruijn H, van Duin R, Huijbregts MAJ (2002) Handbook on life cycle assessment. Operational guide to the ISO standards. Springer, The Netherlands

Haimes YY, Ladson LS, Wismer DA (1971) On a bicriterion formulation of the problems of integrated system identification and system optimization. IEEE Trans Syst Man Cybernetics SMC1 (3):296–297

Hanssen OJ (1999) Status of life cycle assessment (LCA) activities in the Nordic region. Int J Life Cycle Assess 4(6):315–320

Hermans C, Erickson J, Noordewier T, Sheldon A, Kline M (2007) Collaborative environmental planning in river management: an application of multicriteria decision analysis in the white river watershed in Vermont. J Environ Manage 84(4):534–546

Hofstetter P (1998) Perspectives in life cycle impact assessment: a structured approach to combine models of the technosphere, ecosphere and valuesphere. Dissertation, Swiss Federal Institute of Technology Zurich

Hofstetter P, Braunschweig A, Mettier T, Müller-Wenk R, Tietje O (1999) The mixing triangle: correlation and graphical decision support for LCA-based comparisons. J Ind Ecol 3(4):97–115

Huppes G, Sas H, Haan E, Kuyper J (1997) Efficient environmental investments. SENSE Int.Workshop. Centre for Environmental Sciences at Leiden University. http://leidenuniv.nl/interfac/cml/ssp/publications/1997_031.pdf. Accessed 12 Jan 2012

Huppes G, van Oers L, Pretato U, Pennington DW (2012) Weighting environmental effects: analytic survey with operational evaluation methods and a meta-method. Int J Life Cycle Assess 17(7):876–891

Kahneman D, Knetsch JL (1992) Valuing public goods: the purchase of moral satisfaction. J Environ Econo Manag 22(1):57–70

Keeney R, Raiffa H (1976) Decisions with multiple objectives: preferences and value trade-offs. Wiley, New York

Lahdelma R, Salminen P, Hokkanen J (2000) Using multicriteria methods in environmental planning and management. Environ Manage 26(6):595–605

Le Téno JF, Mareschal B (1998) An interval version of PROMETHEE for the comparison of building products' design with ill-defined data on environmental quality. Eur J Oper Res 109(2):522–529

Lesage P, Deschênes L, Samson R (2007) Evaluating holistic environmental consequences of brownfield management options using consequential life cycle assessment for different perspectives. Environ Manage 40(2):323–337

Lindeijer E (1997) Results try-out Japanese/Dutch LCA valuation questionnaire 1996. IVAM (Environmental Research University Amsterdam), Amsterdam

Lippiatt BC, Fuller S (2007) An analytical approach to cost-effective, risk-based budgeting for federal information system security. NIST Interagency Report 7385; National Institute of Standards and Technology (NIST), Gaithersburg

Mettier T, Baumgartner T (2000) A nonmonetary approach to weight environmental damages in life cycle assessment. Dissertation, ESEE 2000, Third Biennial Conference of the European Society for Ecological Economics, Vienna

Nagata K, Fujii Y, Ishikawa M, Yokota R, Ureshino M (1997) Developing an impact assessment methodology using panel data. Dissertation, Workshop on Total Ecobalance. Research Institute for Innovative Technology for the Earth, Tokyo

Norese MF, Toso F (2004) Group decision and distributed technical support. Int Trans Oper Res 11(4):395–417

Onn CC, Yusoff S (2010) The formulation of life cycle impact assessment framework for Malaysia using eco-indicator. Int J Life Cycle Assess 15(9):985–993

Roy B (1991) The outranking approach and the foundations of electre methods. Theor Decis 31(1):49–73

Saaty TL (1980) The analytic hierarchy process: planning, setting priorities, resource allocation. McGraw-Hill, New York

Sabio N, Gadalla M, Jiménez L, Guillén-Gosálbez G (2010) Strategic planning with risk control of hydrogen supply chains for vehicle use under uncertainty in operating costs: a case study of Spain. Int J Hydrogen Energ 35:6836–6852

Sabio N, Kostin A, Guillén-Gosálbez G, Jiménez L (2012) Holistic minimization of the life cycle environmental impact of hydrogen infrastructures using multi-objective optimization and principal component analysis. Int J Hydrogen Energ 37(6):5385–5405

Salminen P, Hokkanen J, Lahdelma R (1998) Comparing multicriteria methods in the context of environmental problems. Eur J Oper Res 104:485–496

Seppälä J, Basson L, Norris GA (2001) Decision analysis frameworks for life-cycle impact assessment. J Ind Ecol 5(4):45–68

Stewart TJ (1992) A critical survey on the status of multiple criteria decision making theory and practice. Int J Mgmt Sci 20(5/6):569–586

Thompson M, Ellis R, Wildavsky A (1990) Cultural theory. Westview Print Boulder, San Francisco

Tietje O, Scholz RW, Heitzer A, Weber O (1998) Mathematical evaluation criteria. Adv Geoecol 31:53–61

Turner RK, Pearce D, Bateman I (1993) Environmental economics: an elementary introduction. Johns Hopkins University Press, Baltimore

Walz R, Herrchen M, Keller D, Stahl B (1997) Ecotoxicological impact assessment and the valuation step within LCA: pragmatic approaches. Fraunhofer-Institut, Karlsruhe

Yoon K, Hwang C-L (1985) Manufacturing plant location analysis by multiple attribute decision making: part I-single-plant strategy. Int J Prod Res 23:345